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ARTICLE

State-contingent production technology formulation: Identifying states of nature using reduced-form econometric models of crop yield

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Abstract

Conducting experiments can be time consuming and expensive, and may not always be reasonable. Therefore, empirical research often derives structural parameters based on observational data and reduced-form econometric models. The state-contingent approach presents a consistent conceptual framework for analyzing producer decisions under uncertainty. However, application of this structural modeling approach has been hampered by data constraints, particularly the lack of information for mapping producers' stochastic outputs onto a set of the states of nature representing different uncertain events. Consistent mapping of uncertainty is particularly critical in the context of multiple output production where weather shocks often have different effects across crops and in microeconometric analyses when unobserved farm heterogeneity may confound the effect of uncertainty. Our study demonstrates how the application of reduced-form approaches can overcome constraints of structural econometric modeling associated with the lack of relevant data and presents an approach for identifying states of nature in the context of multiple output production using reduced-form econometric models of crop yield. In an empirical application based on Hungarian farm accountancy data, we demonstrate that the proposed approach allows a consistent mapping of production uncertainty in crop farming, utilizes panel data structure, and controls for potential endogeneity due to unobserved farm heterogeneity. We anticipate the presented approach to be useful for developing further the state-contingent approach and to stimulate further studies combining the strengths of structural approaches and reduced-form models.

KEYWORDS

identification problem, production analysis under uncertainty, quasi-experimental data, state-contingent approach, structural and reduced-form models

JEL CLASSIFICATION

C18, C23, D81, Q12

1 | INTRODUCTION

The last 2 decades of research on the effect of uncertainty on agricultural producers' decisions and risk management in agriculture have been characterized by a movement away from structural approaches (Tack & Yu, 2021). This development was induced by the "credibility revolution," which disclosed the empirical difficulty of obtaining consistent estimates of structural parameters—a trend that is characteristic for numerous economic disciplines (Tack & Yu, 2021; Angrist & Pischke, 2010). It resulted in much empirical research relying on reduced-form econometric approaches and, accordingly, focusing on the estimation and identification of specific parameters of corresponding structural models.[1]

The lack of full information on underlying structural (data-generating) processes considerably impacts empirical researchers' prospects for drawing consistent inferences (Angrist & Pischke, 2010; Tomek, 1998). At the same time, conducting experiments is time consuming, expensive, and may not always be feasible or an adequate solution. In this context, empirical research often relies on observational (i.e., nonexperimental) data. However, observed variables may not (always) be suitable measures of underlying concepts, or no data may exist for some concepts and processes.[2]

There is potentially no other structural approach in agricultural economics whose application has been as strongly hampered by data constraints as the state-contingent approach. Much of empirical research investigating production decisions under uncertainty and producers' risk preferences continues to rely on the expected utility framework and the stochastic production function approach (Tack & Yu, 2021). In his recent paper, Quiggin (2022, p. 718) emphasizes that "the analytical tools applied to the problem of the firm under uncertainty were derived under the assumption of expected-utility maximization," despite the pathbreaking insight by Debreu that the concept of a state-contingent commodity "allows one to obtain a theory of uncertainty free from any probability concept and formally identical with the theory of certainty" (Debreu, 1959, p. 98, as cited in Quiggin, 2022, p. 718). Quiggin also points at the fact that "little account has been taken of theoretical advances in the theory of choice under uncertainty" in the analysis of production under uncertainty (Quiggin, 2022, p. 722).

Using the Arrow–Debreu conceptual framework for representing uncertainty in terms of a set of states of nature and mapping them onto particular uncertain events, Chambers and Quiggin (2000) have demonstrated that most empirical representations of stochastic technologies, including Just and Pope's (1978) stochastic production function, place severe restrictions on stochastic technology. In this context, Chambers and Quiggin (2000) refer to an "output-cubical technology," that is, a technology characterized by the absence of output substitution across states of nature.

Chambers and Quiggin (2000) have also demonstrated that producers' input use depends on outputs in all possible states of nature, that is, not on singular realized states as is implicitly assumed in the standard stochastic production function framework. Accordingly, considering that observed outputs (in specific periods) are associated with a single state of nature and thus incompletely reflect the effect of production uncertainty, there exists a serious identification problem in modeling producers' decisions under production uncertainty (Chavas, 2008). According to Chavas (2008), "we cannot estimate the ex ante technology without observing all possible outputs (meaning outputs under all possible states, and not just for the realized state)" (p. 439).

In our study, we address this aspect of state-contingent production technology modeling by demonstrating how a reduced-form approach can be applied to address the well-known identification problem associated with the conditioning on observables when deriving causal inferences. To this end, we build on the recent advantages in modeling the reduced-form relationships between weather and crop yields using panel data on historical weather observations and crop yield.

Considering that year-to-year variation in the weather in a fixed location is random and exogeneous to a crop's yield, the reduced-form relationship between ex-post crop yield observations and weather records is clearly identified and can be considered a quasi-natural experiment (Schlenker & Roberts, 2006, 2009). Consequently, reduced-form econometric models of crop yield estimated using farm crop yield data and historical weather observations for the corresponding geographical location can be considered as useful tools for establishing a consistent mapping between a farm's stochastic output and location-specific interannual weather variation.

However, weather shocks often exhibit different effects across crops. A state of nature may be simultaneously favorable for producing one output (or several outputs) and unfavorable for another output (or some other outputs). In this setting, producers often allocate inputs to the production of outputs/crops that demonstrate different degrees of sensitivity to specific weather events. Thus, state-contingent outputs depend on both the realized states of nature and on farmers' efforts aimed at reducing the effect of production uncertainty on farm output (Chambers & Quiggin, 2000). Consequently, ignoring farmers' actions, such as portfolio diversification, may hinder the identification of production uncertainty's effect on production technology. To address this aspect, we propose a mapping procedure that considers each state's effects on specific farm outputs/crops.

Furthermore, a consistent mapping of individual producers' production outcomes onto a set of uncertain events may be particularly complicated in the context of microeconometric analyses. This is because the impact of production uncertainty on state-contingent outputs can be confounded by unobserved farm heterogeneity. Specifically, the same input combination may produce different amounts of output under the same state of nature in the presence of unobserved farm heterogeneity.[3] In this context, it is important to employ a mapping procedure that considers panel data structure and allows application of the estimation methods addressing omitted variable endogeneity. In an empirical application based on a panel dataset for a sample of Hungarian cereal producers, we demonstrate that the proposed approach utilizes panel data structure and enables us to control for potential endogeneity bias.

In the subsequent section, we summarize the aspects that have been addressed in previous empirical applications of the state-contingent approach. Additionally, we provide a short overview of the recent advances in the modeling weather–yield relationships using reduced-form models. Section 3 describes the methodological framework applied in the study, including the proposed empirical strategy for mapping production uncertainty and the state-contingent production technology formulation employed in the empirical application. Section 4 presents the data and empirical procedure used in our empirical application and summarizes its main results. The final section concludes.

2 | RESEARCH BACKGROUND

2.1 | Empirical applications of the state-contingent approach

Only a few studies have applied the state-contingent approach to modeling producer behavior under uncertainty. Most studies in this line of the literature have explored options to resolve identification problems associated with empirical implementation of the state-contingent approach.

In this context, Chavas (2008) refers to serious identification problems when only one particular outcome is observed for each period/study unit, that is, in the absence of information/knowledge about all possible outcomes/states of nature. He also cautions of potential identification bias in situations where one single factor/indicator is used to distinguish between specific states of nature, as such a representation of production technology imposes separability of the stochastic factors determining output uncertainty (Chavas, 2008). In addition, O'Donnell and Griffiths (2006) draw attention to the fact that variables representing states of nature typically remain unobserved to the researcher. Nauges et al. (2011); henceforth, NOQ (2011) refer to identification problems, which may arise in the context of cross-sectional or panel data. In particular, by defining generic states of nature, such as "good," "normal," and "bad," empirical studies risk ignoring the fact that states of nature may differ from producer to producer, for example, a good state for one farmer may be another farmer's normal state.

To address the identification problem, different empirical strategies have been developed in the state-contingent literature. O'Donnell and Griffiths (2006) present an approach involving a Bayesian latent class model to estimate a state-contingent stochastic frontier model subject to rainfall uncertainty. In their empirical application, the authors show that when state-contingent uncertainty plays a major role, the standard stochastic frontier approach may significantly overestimate producers' technical inefficiency.

Chavas (2008) proposes an approach for estimating cost-minimizing input choices with two states of nature and testing the assumption of output-cubical technology in the context of a time series analysis. In particular, based on an aggregated crop yield index, he specifies an auxiliary function to simulate for each period potential states of nature to represent production uncertainty in the context of United States (U.S.) agriculture. Chambers and Serra use an akin econometric procedure to identify two states of nature in the context of output price uncertainty.[4]

To address the issue of missing information on relevant stochastic prospects, Chambers et al. (2015) have proposed a mapping strategy involving expert knowledge and a farm survey. Although this empirical strategy presents several advantages, such as a direct elicitation of producers' subjective expectations, it may also be susceptible to identification bias, for example, if respondents apply inconsistent mapping rules and/or their assessments are subject to measurement errors. Moreover, if the degree of subjectivity and respectively probability assessments for generic states of nature formulations such as "good" and "bad" vary substantially across producers, embedding producers' subjective assessments may lead to a biased representation of production uncertainty and consequently threaten identification.

Interestingly, most empirical studies have failed to reject the assumption of output-cubical technology that excludes output substitutability across states of nature. To the best of our knowledge, NOQ's (2011) study is the only investigation that provides empirical support for output substitutability between different states of nature. NOQ (2011) define states of nature for Finnish grain producers using two indicators of weather conditions, specifically, the season-specific start date of the growing period, and the cumulative rainfall in June. To this end, they compare average crop yields (computed using their farm data) under different weather conditions, as represented by the two above-mentioned weather indicators. Subsequently, they assign each farm-year observation a specific state of nature subject to the corresponding observed values of the selected weather indicators.[5]

Another distinctive feature of NOQ's (2011) research is that it was the first study to that formulated states of nature in the context of multiple output production. Although it employs a production function formulation with one aggregate output, their model distinguishes between land input allocations to three different crops. However, NOQ (2011) define their states of nature in terms of their suitability for growing one particular crop that is a rather restrictive assumption considering that weather conditions in a production period may be simultaneously favorable for several crops grown by a farmer.[6]

An overview of the main state-contingent technology formulations used in the literature can be found in Shankar (2012).

2.2 | Reduced-form econometric models of crop yield

Statistical crop yield models have been extensively used over the past decade to investigate the impact of climate change on agricultural productivity (e.g., Ortiz-Bobea & Just, 2012; Roberts et al., 2012; Schlenker & Roberts, 2009; Tack et al., 2015). This recent research goes back to the work by Mendelson et al. (1994), who proposed to regress land values on a set of weather variables in order to identify the net impacts of climate on agriculture. As crop yields are better suited to represent the impacts of weather variation on agricultural productivity and at the same time show high correlations with economic outcomes, recent research on the topic focused on improving the capacity of statistical crop yield models to provide consistent estimates of the weather–yield relationship.

Furthermore, Schlenker and Roberts (2006) refer to a serious limitation of cross-sectional approaches to modeling the impact of climate change on an economic outcome such the Ricardian approach by Mendelsohn et al. (1994). Particularly, cross-sectional approaches may be susceptible for the omitted variables problem. As it is hardly possible to include into the model all relevant factors potentially correlated with the current climate, cross-sectional approaches may confound climate with other factors and, thus, provide biased estimates. To address this problem, in their study on nonlinear effects of weather on county-level corn yields, Schlenker and Roberts (2006) formulate a panel model with the county fixed effects. According to these authors, "The use of fixed effects avoids the problem of omitted variables, as they are lumped together in the fixed effects." (Schlenker & Roberts, 2006, p. 393). Accordingly, by capturing time-invariant heterogeneity across study units through the introduction of fixed effects, reduced-form panel models of crop yield allow identification of the effects of interannual weather variation on crop yields. This explains why recent studies on the topic have applied mainly fixed-effects model formulations of crop yield models (Ortiz-Bobea & Just, 2012; Roberts et al., 2012; Schlenker & Roberts, 2009; Tack et al., 2018).

Important contributions in this line of literature addressed aspects such modeling nonlinear temperature effects and impacts of extreme heat on crop yields (Schlenker & Roberts, 2006, 2009; Tack et al., 2015), a more explicit consideration of adaptation processes (Burke & Emerick, 2016; Ortiz-Bobea & Just, 2012), identifying weather-driven changes for different moments of crop yield distributions (Tack et al., 2012), and controlling for endogeneity of prices in yield and land use regression models (Miao et al., 2016).

To model the impact of heat on crop yields, Schlenker and Roberts (2006, 2009) propose to measure the time a crop is exposed to each 1°C temperature interval during a day (i.e., degree days). By using yields for corn, soybean and cotton and daily weather records for the U.S. counties, Schlenker and Roberts (2009) have shown that yields increase with temperature up to 29°C for corn, 30°C for soybeans and 32°C for cotton, and decrease sharply above these thresholds for all three study crops.

Schlenker and Roberts (2006, p. 391) argue that reduced-form models of weather–yield relationships formulated using location-specific weather observations (which are random and exogeneous) can be considered as a natural experiment. Furthermore, they refer to the superiority of their approach allowing to evaluate non-linear temperature effects on crop productivity and to derive "the consummate effects of weather on yields" compared to the reduced-form approaches that "ignore the distribution of weather realizations around their averages," for example, crop model formulations employing average daily temperature and cumulative precipitation for single months of plant vegetation (Schlenker & Roberts, 2006, p. 392).

More recently, Massetti et al. (2016) showed that for agricultural production in the United States degree days and temperature variables are perfect substitutes over the growing season. Massetti et al. (2016) also show that the effect of temperature is not the same in each season. Considering this finding, they stress that aggregating temperature measures over a crop's entire growing season may miss the specific effects of meteorological seasons. Empirical results of the study on the impact of warming temperatures on U.S. winter wheat yields by Tack et al. (2015) support this argument. Specifically, they indicate that the sensitivity of winter wheat to temperature exposure varies considerably over the meteorological seasons considered in their study (i.e., fall, winter and spring). Tack et al. (2015) refer also to differences in the shape of the precipitation effects on winter wheat yields across spring and autumn.

Ortiz-Bobea and Just (2012) draw attention to that even season-long weather variables may fall short to capture adequately varying sensitivity of plants to weather at different phenological stages and recommend to formulate weather variables based on existing scientific knowledge of the underlying mechanisms of the weather impact on production. In their empirical example, they use a statistical corn yield model with weather variables measured for the key stages of the corn phenology. This procedure allows them to estimate model coefficients that are not fixed to calendar periods but single stages of plant growth, which can move with shifts in growing seasons induced by climate change.

Whereas most studies predict climate change impacts on crop yield conditional means, Tack et al. (2012) propose an approach enabling weather effects to be evaluated using conditional higher order moments of the yield distribution, as raising temperatures may change not only expected yields but also the shape of yield distributions. Subsequently, they propose utilizing the moments of the distribution estimated using the maximum entropy method to construct yield distribution under selected climate and irrigation regimes.

Recent research on modeling the weather–yield relationship advanced the capacity of reduced-form crop yield models to infer the impact of weather variation on crop yields and made them a powerful tool for identifying weather-related production uncertainty in crop farming. The most recent review of the methods used in this research line can be found in Ortiz-Bobea (2021).

3 | METHODOLOGY

3.1 | Formulation of states of nature

Basic features of states of nature

Chambers and Quiggin (2000, pp. 17–18) describe a comprehensive set of states of nature as “a mutually exclusive and exhaustive set of possible descriptions of the state of the world.” Simultaneously, they claim that a complete description is impossibly complex, which is why the state space must disregard those features of the environment that are irrelevant to the problem under consideration and instead capture only those features that are pertinent. Additionally, they define the state space as a Cartesian product of all pertinent characteristics of the environment.

Furthermore, Chambers and Quiggin (2000) underline the importance of considering decision-makers’ actions aimed at addressing production uncertainty. Accordingly, they distinguish between the states of nature (i.e., states of the world/environment) and outcome states that are formulated based on the outcomes of a production process. Considering that production outcomes are determined based on both states of nature and decision-makers’ actions, using data on observed outputs to formulate states of nature will, indubitably, cause an identification problem. Moreover, Chambers and Quiggin state that if the outcome for any action undertaken by a decision maker remains the same across a number of states of nature under consideration, they can be collapsed into a single state of nature (2000, p. 18).

In our study, we build on these basic features of states of nature summarized by Chambers and Quiggin (2000) to develop an empirical strategy for formulating states of nature in a multiple output production context.

Multiple outputs and multiple uncertain events

To manage production uncertainty, farmers usually produce outputs/crops with varying degrees of sensitivity to different weather events. They frequently select crops that demonstrate significant differences in growing periods and phenology, for example, winter grains and spring grains. Accordingly, diverse sets of weather events may be relevant for growing different crops and must be, therefore, considered when mapping relevant sources of production uncertainty in a multiple output production context.

Consider the following example: A farmer specializes in the production of a specific crop (e.g., a spring grain) that exhibits high sensitivity to drought in June; let us call it Crop 1. To reduce this source of production uncertainty, the farmer may decide to produce another crop, such as a winter grain, which we call Crop 2. Compared to Crop 1, Crop 2 exhibits lower sensitivity to drought. However, Crop 2 is more prone to another source of production uncertainty—extensive rainfall in late fall—which is on its part not of great relevance for growing Crop 1. In this context, the farmer must decide about the amount of land and other inputs to be allocated to the production of each of the two crops. Accordingly, the farmer's ex-ante decision regarding input allocation to Crop 1 depends on their assessment of the production uncertainty for both Crop 1 and 2. Effectively, as presented in Table 1a, the farmer must make their input allocation decisions considering the uncertain events pertinent for growing both crops.

Furthermore, considering that, typically, multiple sources of production uncertainty exist in agriculture, it is important to capture their joint effect on output during a production period. Referring to the previous example, imagine that the productivity of Crop 2 is contingent not only on extensive rainfall in late fall but also the temperature and rainfall regime in early spring (because cold and rainy weather in March and April may kill young plants). Consequently, the state space presented in Table 1a must be adjusted to account for this additional source of production uncertainty for Crop 2 to adequately capture the effects of production uncertainty. This modified example is summarized in Table 1b.

The above-presented examples emphasize the following: First, states of nature should reflect the weather outcomes that are relevant to growing all major crops/outputs produced on a farm. Second, in the presence of several uncertain events, states of nature formulations should account for their joint (cumulative) impacts on the productivity of the respective crop. Third, in a multiple output production context with multiple uncertain events, the dimension of the state space may increase considerably for each additional study crop and uncertain event. This aspect requires a procedure that allows state space dimensionality reduction without forcing abstraction from relevant characteristics of the environment. The latter is however a desirable property only when producers do not undertake distinct efforts to address a particular uncertain event.

Another aspect to be considered when formulating states of nature in a multiple output production context is that producers' actions aimed at exploiting potential substitution between different output types may significantly influence output substitutability across states of nature. This consideration requires a production technology representation that enables the modeling of multiple output correspondence with both the formulated states of nature and varying input bundles applied by producers.

3.2 | Identifying states of nature based on reduced-form models of crop yield

We believe that recent advances in the modeling weather–yield relationships have made reduced-form econometric models of crop yield to powerful tools for mapping weather-related production uncertainty in agriculture. First, they are helpful in identifying weather events that significantly influence the productivity of specific crops. Second, they allow one to capture the complex relationships between crop yields and diverse weather events and enable assessments of their joint (cumulative) effect. Accordingly, the resulting conditional yield estimates can be used to derive a relatively compact set of weather characteristics/outcomes that capture the joint effects of multiple weather events. Finally, using panel approaches for modeling crop yield responses to interannual weather variation may help establish consistent correspondence

TABLE 1A Specification of the state space for the example with two crops and two sources of production uncertainty.

		Crop 1	
		Drought in June (DJ)	No drought in June (NDJ)
Crop 2	Extensive rainfall (ER) in late autumn	DJ, ER	NDJ, ER
	No extensive rainfall (NER) in late autumn	DJ, NER	NDJ, NER

TABLE 1B Specification of the state space for the example with two crops and three sources of production uncertainty.

			Crop 1	
			Drought in June (DJ)	No drought in June (NDJ)
Crop 2	Extensive rainfall (ER) in late autumn	Unfavorable rainfall-temperature regime in early spring (URTS)	DJ, ER & URTS	NDJ, ER & URTS
		Favorable rainfall-temperature regime in early spring (FRTS)	DJ, ER & FRTS	NDJ, ER & FRTS
	No extensive rainfall (NER) in late autumn	Unfavorable rainfall-temperature regime in early spring (URTS)	DJ, NER & URTS	NDJ, NER & URTS
		Favorable rainfall-temperature regime in early spring (FRTS)	DJ, NER & FRTS	NDJ, NER & FRTS

between sample farms' production data and annual weather records for corresponding locations (e.g., grids showing a farm's location).

To identify weather events that explain a considerable part of year-to-year variation in farm crop yields, we propose using the following basic reduced-form crop yield model formulation:

$$\ln y_{jit} = \mathbf{w}'_{jit}\boldsymbol{\beta}_j + u_{ji} + f_j(t) + \epsilon_{jit}, \quad (1)$$

where y_{jit} is the yield of crop $j = 1,\ldots J$ in farm $i = 1,\ldots N$ and year $t = 1,\ldots,T$; $\mathbf{w}_{jit}$ is the vector of relevant weather variables for crop j, computed using weather records for farm i's location; and $\boldsymbol{\beta}_j$ is the vector of the corresponding coefficients. u_{ji} are farm fixed effects used to control for time-invariant (omitted) factors that may confound the weather impact on crop yields (Schlenker &

Roberts, 2006), $f_j(t)$ are crop-specific time trends employed to capture the technical change effect, and ϵ_{jit} is the stochastic error term.

The model in Equation (1) can be consistently estimated using e.g. Conley's heteroskedasticity and spatial and serial correlation consistent (HAC) estimator (Conley, 1999; Hsiang, 2010) or a spatial error model (SEM) (Ortiz-Bobea, 2021).[7] In our empirical application, we apply Conley's estimator, which is used more frequently than the SEM estimator (Ortiz-Bobea, 2021).

Subsequently, we use estimates of the model in Equation (1) for major (specific) crops produced by sample farms, to derive quasi-experimental observations of crop yields. Akin to the approach proposed by Chavas (2008), in the context of a time series analysis and aggregate production output, we propose to capture production uncertainty by an auxiliary yield index. However, instead of employing a single auxiliary index derived using an aggregate yield index, we derive crop-specific auxiliary yield indices. Considering the model formulation in Equation (1), we define them as follows:

$$h_{jit} = \exp\left(\mathbf{w}'_{jit}\boldsymbol{\beta}_j\right). \tag{2}$$

Equation (2) demonstrated that h_{jit} is derived based on the conditional mean of crop j, using historical realizations for the vector of weather variables $\boldsymbol{w}$ in Equation (1). Given the exogenous nature of weather and consistency of estimates obtained from the fixed-effects model formulation in Equation (1), h_{jit} consistently captures the effect of interannual weather variation on respective crop yields for each sample farm-year observation and can be considered as quasi-experimental data capturing the impact of weather-related production uncertainty.

After deriving h_{jit}, a straightforward mapping of the weather-related production uncertainty (associated with the production of each specific crop) can be established by splitting the corresponding h_{ji} distribution into K_j intervals[8]: $r_{ji1} = \left(-\infty, q_{ji1}\right), r_{ji2} = \left(q_{ji1}, q_{ji2}\right), \ldots, r_{jiK_j} = \left(q_{jiK_j-1}, \infty\right)$, where $q_{ji1} < q_{ji2} < \ldots < q_{jiK_j-1}$ could be particular selected quantiles or other measures of location of auxiliary index distribution for crop j and farm i over the period under consideration. This procedure helps us determine for each sample farm and study crop a set of K_j nonoverlapping auxiliary index intervals representing crop-specific weather outcomes.

Then, we define our state space as a Cartesian product of the sets of crop-specific weather outcomes. Considering J crops with K_j intervals each, it comprises $S = \prod_{j=1}^{J} K_j$ intersections of all identified weather outcomes/auxiliary index intervals. For example, in the case of three crops with two nonoverlapping intervals each—namely, (i) below than or equal to, and (ii) above the respective auxiliary index threshold, such as the mean or the median, the state set would comprise a total of eight states of nature.[9]

In Figure A1 of the Appendix, we present the aforementioned procedure using a basic hypothetical example with two crops having two weather outcomes each. We also use this example to exemplify the construction of two types of dummy variables, namely, states of nature dummy variables e_s $(s \in S = 4)$ and weather-outcome dummy variables $e_{jk_j}(k_j \in K_j = 2)$. In our empirical application we show, how this type of variables can be used for the operationalization of an empirical model of state-contingent production technology.

The presented strategy for mapping production uncertainty allows states of nature to be favorable for growing one particular crop and unfavorable for all other crops grown by a farmer—a mapping rule used by NOQ (2011). Concurrently, it does not exclude situations wherein a state of nature can be simultaneously favorable for a number of crops produced on a farm. It neither exclude situations wherein the sources of production uncertainty may vary across different farm outputs.

Further, this approach for formulating states of nature can be extended to consider other sources of uncertainty, such as disease or pest damages, which can also be crop specific.[10]

3.3 | State-contingent technology model with technical inefficiency

To exemplify the proposed approach for mapping states of nature, we apply a production-function model that builds upon the state-contingent production technology representation proposed by O'Donnell et al. (2010)[11]:

$$\ln q_s = b^{-1}(\ln x_s - \ln a_s), \tag{3}$$

where q_s denotes output realized under state of nature s ($s \in \Omega = 1,2,\ldots$, S); x_s is the amount of non-stochastic input allocated to state s; parameters $a_s \geq 0$ are interpreted as technical parameters specific to the production of output in state of nature s. Further, b can be interpreted as the cost flexibility indicator and expresses the magnitude of output substitutability across states of nature. b is restricted to be greater than unity, which implies that the technology exhibits nonincreasing returns to scale (OCQ, 2010).

Based on Equation (3), the state-specific input requirement function is defined as the amount of the input that must be committed in period 0 if output q_s is to be realized when Nature chooses s from Ω, viz.:

$$x_s = a_s q_s^b. \tag{4}$$

In a basic case with two states of nature, the producer must allocate ex ante a total input amount $x = x_1 + x_2$ to a specific state of nature. This enables them to produce q_1 when Nature draws $s = 1$ and q_2 when Nature draws $s = 2$ (QCO, 2010):

$$a_1 q_1^b + a_2 q_2^b \equiv g(q_1, q_2). \tag{5}$$

Technically feasible production patterns are then defined by introducing a convex transformation function:

$$t(q_1, q_2, x) = g(q_1, q_2) - x. \tag{6}$$

Accordingly, the producer is technically efficient if $t(q_1, q_2, x) = 0$ and technically inefficient if $t(q_1, q_2, x) < 0$. Expressed in terms of the input distance function, this corresponds to

$$D_I(x, q_1, q_2) = \frac{x}{g(q_1, q_2)}, \tag{7}$$

where $D_I = 1$ for technically efficient producers, and $D_I > 1$ for technically inefficient producers.

The output-oriented efficiency measure for the technology formulation in Equation (4) has the following form:

$$D_O(q_1, q_2, x) = g(q_1, q_2)^{\frac{1}{b}} x^{-\frac{1}{b}}, \tag{8}$$

that is the constant elasticity of transformation (CES) output distance function (OCQ, 2010). In this case, $D_O = 1$ for technically efficient producers, and $D_O < 1$ for technically inefficient producers.

The above-presented model of a state-contingent technology assumes that the vector of state-contingent outputs is known, in particular, the effect of uncertainty on producer's output is identified by the set (q_1, q_2). It also assumes that the inputs are state specific, that is, an input allocated to a given state of nature contributes to the production of output only in that particular state of nature (Shankar & Quggin, 2013).

OCQ's (2010) model was extended by NOQ (2011, Equation (4)) to a more flexible CES-type model, differentiating between one state-allocable input, x_s, and a vector of non-state-allocable inputs z_p:

$$q_s = A_s \left[\theta^b x^b + \delta_s^b x_s^b + \sum_{p=1}^{P} \gamma_p^b z_p^b \right]^{\phi/b}, \tag{9}$$

where $x = \sum_{s=1}^{S} x_s$ is the total use of the state-allocable input[13], which allows the production output to be nonzero in state of nature s even if no input is allocated to this state; δ_s is a measure of how production output in state s responds to an input allocation to that particular state. Finally, $b \neq 0$; $\phi > 0$ and $A^s \equiv a_s^{-1/b} \geq 0$.[14]

The production technology as defined in Equation (9) can exhibit increasing, constant, and decreasing returns to scale (RTS) subject to the value ϕ, corresponding to $\phi < 1, \phi = 1$ and $\phi > 1$, respectively. The supply elasticities for the state-allocable input in individual states of nature can be derived by differentiating the expression in Equation (9) by the variable representing the allocation of this input to the corresponding state of nature, x_s (NOQ, 2011):

$$\frac{\ln q_s}{\ln x_s} = \frac{\phi \left(\theta^b \mathrm{x}^{b-1} x_s + \delta_s^b x_s^b \right)}{\theta^b x^b + \delta_s^b x_s^b + \sum_{p=1}^{P} \gamma_p^b z_p^b}. \tag{10}$$

To estimate the model presented in Equation (9) using observational data on ex-post output realizations, NOQ (2011) attribute ex-post output observations to a total of three pre-identified states of nature using information regarding weather suitability for growing different study crops. Particularly, they assigned observations on their state-allocable input to specific states of nature using a state dummy variable e_s, which takes value 1 when Nature chooses state s, and 0 otherwise. Accordingly, they rewrite the model in Equation (10) as follows:

$$\ln q = \sum_{s=1}^{S} e_s \ln A_s + \ln \left[\theta^b x^b + \sum_{s=1}^{S} \delta_s e_s x_s^b + \sum_{p=1}^{P} \gamma_p^b z_p^b \right]^{\phi/b}, \tag{11}$$

In contrast to the models in Equations (3) and (7)–(10), wherein state-contingent outputs are known, the model in Equation (11) is formulated in terms of ex-post realizations of producers' stochastic outputs that correspond with states of nature unknown to the researcher. To solve the identification problem, NOQ (2011) define farmers' stochastic outputs being conditional on both the input use and S states of nature identified externally to the model. As mentioned earlier, the information on states of nature is inputted into the model using the dummy variable e_s.

Chambers and Quiggin (2000) refer to this technology formulation as a state-contingent production function and describe it using the following general notation: $q = f(x\mathbf{1}^S)$, where x is a quasi-fixed input chosen by the farmer prior to Nature's draw from the state space, and $\mathbf{1}^S$ is an S-dimensional unit vector. O'Donnell and Griffiths (2006) propose expressing this production function model, defined as a stochastic frontier, as $lnq = f_s(x) - \mathrm{u}$,[15] to stress that, in this technology formulation, for each state of nature there exists its own state-contingent production function.

Another important feature of the model in Equation (11) is that it assumes separability.[16]

3.4 | State-contingent frontier model formulation for panel data

To exemplify the identification strategy presented in Section 3.2, we rewrite the model in Equation (11) as follows:

$$q_{it} = \sum_{s=1}^{S} e_s A_s \Bigg) \left[\theta^b x_{it}^b + \sum_{s=1}^{S} \sum\nolimits_{j=1}^{J} \delta_{sj}^b e_s x_{jit}^b + \sum_{p=1}^{P} \gamma_p^b z_{pit}^b \right]^{\phi/b}, \tag{12}$$

where $i=1,\ldots,N$ and $t=1,\ldots,T$ are the farm and time subscripts, respectively. x_{jit} denotes land allocated to crop $j=1,\ldots,J$ in farm i and period t, and $x_{it}=\sum_{j=1}^{J} x_{jit}$ is the total land use in the respective farm and period. s ($s=1,\ldots,S$) denotes one particular of S states of nature, and e_s is a dummy variable that takes value 1 if Nature selects in the location of farm i in year t state of nature s and 0 otherwise.

The main difference between the models in Equations (12) and (11) is the way of formulating the states of nature. Using quasi-experimental data to summarize the effects of interannual weather variation on productivity of specific crops grown by sample farmers, we can formulate the states of nature by considering their effects on different crops grown in sample farms. Specifically, we can account for the fact that weather conditions in the same production period may be either simultaneously favorable or unfavorable or have diverging effects on productivity of two or more crops grown by a farmer. Accordingly, the δ-parameters in the model in Equation (12) vary across both states of nature and crops, and consequently denoted as δ_{sj}.

The technology formulation in Equation (12) requires the estimation of an SJ-dimensional vector of δ-parameters measuring how the output in state s responds to the allocation of land to crop j. Moreover, it requires a set of restrictions to ensure identification; particularly, the δ-parameters for crop j cannot differ across those states of nature, which accommodate the same weather outcome for that crop. Herein, we exemplify this aspect using a simple example with two crops as follows: Crop 1 ($j=1$) and Crop 2 ($j=2$), each having two coarse weather outcomes—"unfavorable" ($k_j=1$) and "favorable" ($k_j=2$). In this example, our approach for formulating states of nature results in a total of four states: two states, bearing the predicates "unfavorable," and two states, bearing the predicate "favorable," for each crop. Let us define $s=1$ as the combination of weather outcomes unfavorable for both crops, $\{k_{j=1}=1, k_{j=2}=1\}$; $s=2$ as the combination of weather outcomes unfavorable for Crop 1 but favorable for Crop 2, $\{k_{j=1}=1, k_{j=2}=2\}$; $s=3$ as the combination of weather events favorable for Crop 1 but unfavorable for Crop 2, $\{k_{j=1}=2, k_{j=2}=1\}$; and $s=4$ as the combination of weather outcomes favorable for both crops, $\{k_{j=1}=2, k_{j=2}=2\}$. Accordingly, the following restrictions on the set of δ-parameters would be required: $\delta_{j=1s=1}=\delta_{j=1s=2}$; $\delta_{j=1s=3}=\delta_{j=1s=4}$; $\delta_{j=2s=1}=\delta_{j=2s=3}$ and $\delta_{j=2s=2}=\delta_{j=2s=4}$.

However, it is possible to derive a more efficient estimator by reformulating the model in Equation (12) as follows:

$$q_{it} = \sum_{s=1}^{S} e_s A_s \Bigg) \left[\theta^b x_{it}^b + \sum_{j=1}^{J} \sum\nolimits_{r_j}^{K_j} \delta_{jk_j}^b e_{jk_j} x_{jit}^b + \sum_{p=1}^{P} \gamma_p^b z_{pit}^b \right]^{\frac{\phi}{b}}, \tag{13}$$

where e_{jk_j} is a dummy variable referring to a specific weather outcome/auxiliary index interval $k_j=1,\ldots,K_j$ for crop j.

In the model in Equation (13), the δ-parameters directly refer to corresponding weather outcomes k_j, forming our state space. Therefore, we can define $\delta_{jk_j}=\delta_{js}, \forall k_j \in s$. Accordingly, compared to the model in Equation (12), the number of δ-parameters can be reduced in this model to $\sum_{j}^{J} K_j$, that is, by $JS - \sum_{j}^{J} K_j = J\prod_{j=1}^{M} K_j - \sum_{j}^{J} K_j$ parameters. For the above-presented example with four states of nature each formed by two specific weather outcomes, this model formulation would involve four parameters less than the model in Equation (12).

By differentiating for each crop j between K_j subsets, each associated with a specific weather outcome,[17] the model in Equation (13) allows deriving, in addition to the marginal rate of technical substitution (MRTS) of the total land input between each pair of states, the MRTS of land allocated to crop j between each pair of states accommodating district weather outcomes for that crop, $k_j = l$ and $k_j = m$ ($m \neq l$), as $\frac{\partial q/\partial x_j \big|_{e_{jk_j=l}}}{\partial q/\partial x_j \big|_{e_{jk_j=m}}}$.

To demonstrate our empirical strategy for mapping production uncertainty, we utilize a special case of the model in Equation (11), referred to in NOQ (2011) as FLEX0.[18] NOQ (2011) formulate it as a stochastic frontier model, viz.:

$$\ln q = \sum_{s=1}^{S} \ln A_s e_s + \theta \ln x + \sum_{s=1}^{S} \delta_s e_s d_s \ln x_s + \sum_{p=1}^{P} \gamma_p g_p \ln z_p + v - u, \tag{14}$$

where $b \to 0$ and $\phi = 1$; e_s is a dummy variable that takes value 1 if Nature picks state s, and 0 otherwise; $d_s = I(x_s > 0)$ and $g_s = I(z_s > 0)$ are indicator functions that take value 1 if the argument is true, and 0 otherwise (NOQ, 2011).[19]

NOQ (2011) have proposed the use of the following parameterization: $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ to estimate the model as a stochastic frontier model. Additionally, they have assumed that the stochastic error term in this model subsumes any errors associated with the fact that it presents a limiting case of the model in Equation (11).

We augment the model in Equation (14) as follows:

$$\ln q_{it} = \sum_{s=1}^{S} e_s \ln A_s + \theta \ln x_{it} + \sum\nolimits_{j=1}^{J} \sum_{k_j=1}^{K_j} \delta_{jk_j} e_{jk_j} d_j \ln x_{jit} + \sum_{p=1}^{P} \gamma_p g_p \ln z_{\text{pit}} + c_t + v_{it} - u_{it}, \tag{15}$$

where $d_j = I\left(x_{jit} > 0\right)$ and $g_p = I\left(z_{pit} > 0\right)$ are indicator functions that take value 1 if the respective condition in parentheses is fulfilled, and 0 otherwise. Year fixed effects c_t control for factors that are constant across farms but vary over time including the effect of technical change. The remaining variables and indices are specified in the same way as in the model in Equation (12).

To control for time-invariant unobserved heterogeneity, we rewrite the model in Equation (15) as the true fixed effects (TFE) stochastic frontier model (Greene, 2005) as follows:

$$\ln q_{it} = \omega_i + \sum_{s=2}^{S} e_s \ln A_s + \theta \ln x_{it} + \sum\nolimits_{j=1}^{J} \sum_{k_j=1}^{K_j} \delta_{jk_j} e_{jk_j} d_j \ln x_{jit} + \sum_{p=1}^{P} \gamma_p g_{pit} \ln z_{pit} + c_t + v_{it} - u_{it}, \tag{16}$$

where ω_i are farm fixed effects. In this model formulation, $s = 1$ is the reference state of nature; accordingly, the estimate of technical parameter $\ln A_1$ coincides with the fixed effect for the reference farm in the sample. Further, it is assumed that u_{it} is i.i.d. $N^+(0, \sigma_u)$; v_{it} is i.i.d. $N(0, \sigma_v)$, and u_{it} and v_{it} are independently distributed.

Akin to the procedure proposed by NOQ (2011), we conduct the test for an output-cubical technology by testing $H0: \delta_{jk_j} = 0, \ \forall j = 1, \ldots, J$ and $\forall k_j = 1, \ldots, K_j$, which implies the absence of substitution between states of nature.

3.5 | An empirical application

We conduct our empirical analysis using accounting data of Hungarian farms specialized in cereal production. Hungarian crop farms are known to face considerable yield risk, predominantly due to droughts (Zubor-Nemes et al., 2018), and are therefore well-suited for studying production uncertainty's effect on farm input allocation decisions. Another important aspect of our empirical analysis is that the Hungarian National Farm Accountancy Data Network (FADN) database contains information on farms' geographical coordinates, allowing farm-level data to be linked to corresponding weather records.

3.6 | Data

We use Hungarian national FADN data for the period from 2002 to 2013 to form an unbalanced sample of specialized cereal farms. Maize and winter wheat are the two main cereal crops produced in Hungary. Together, they account for approximately 90% of the country's cereal output and around 40%–42% of the national crop output (Eurostat, 2019). The sample of study farms contains 2288 observations, with each sample farm represented by at least six annual observations.

We specify farm output using the FADN variable "Total farm output." We measure the total land input in hectares of utilized agricultural area (UAA) and treat it as a quasi-fixed but allocable input. Particularly, we distinguish between three different land allocations, corresponding to the following three farm outputs: maize, winter wheat, and *other farm output*. The latter is defined as the farm UAA after deducting maize and winter wheat crop areas.

The vector of the non-state-allocable inputs consists of labor input, capital, and materials. Labor input is defined as annual work unit, whereas depreciation and expenditures for contractors services (contact work) are used to proxy capital. Total specific costs are used to measure materials input. All monetary indicators are deflated using the price indices provided by the Eurostat (Eurostat, 2019). Farm output is deflated using the price index for total agricultural output; the price index of goods and services contributing to agricultural investment is used to deflate fixed assets; and the price index for goods and services currently consumed in agriculture is employed to deflate materials.

To estimate statistical crop yield models, we use data on farm-level maize and winter wheat yields, whereas the *other farm output* variable is normalized by the difference between the farm UAA and maize and winter wheat crop areas. We also utilize information on each farm's spatial location (grid value) to compute relevant weather variables using gridded agro-meteorological data from Agri4Cast, an agro-meteorological database maintained by the European Commission Joint Research Centre (Agri4Cast, 2019).[20] Summary statistics of all the variables used in the empirical analysis are presented in Table A1 of the Appendix.

3.7 | Empirical procedure

First, we estimate the fixed-effects crop yield model in Equation (1) for maize, winter wheat and *other farm output*. Here, we use the following two alternative sets of weather variables: formulation F1 employs average daily temperature and cumulative precipitation variables computed for crop-specific phenology periods[21]; formulation F2 is based on degree days and cumulative precipitation variables measured for the following periods of crop vegetation: (i) autumn (September–November), winter (December–February), and spring (March–May) for winter wheat following Tack et al. (2015), and (ii) the 6 months of the growing period of maize following Schlenker and Roberts (2009) and the more recent study by Tack et al. (2018), that is April through September in Hungary. For wheat, we measure degree-days variables using the same temperature intervals as Tack et al. (2015, Table S3 in the supplementary materials). For maize, we employ the thresholds of 10°C and 30°C, that is, the same lower threshold as Schlenker and Roberts (2009) but a 1°C higher upper threshold than used in that study.[22] We use the growing degree days (GDD) corresponding with the temperature interval between 10°C and 30°C, and the heating degree days (HDD) above 30°C for modeling crop yields for both maize and *other farm output*.

Considering that both crop yield model formulations (F1 and F2) did not provide statistically significant response estimates for *other farm output*[23], we formulate auxiliary yield indices and subsequently the state space using only crop model estimates obtained for maize and winter wheat. Additionally, formulation F2 of the crop yield model for winter wheat did neither provide statistically significant estimates.[24] Therefore, we compute the auxiliary yield index for winter wheat solely based on model formulation F1.

The final crop yield model specifications and estimation results for maize and winter wheat can be found in Tables A2-1, A2-2, and A3 of the Appendix, respectively.[25]

Second, we use crop yield model estimates to derive auxiliary yield indices h_{jit} as presented in Equation (2). Because weather records are available for farm specific locations (grids) and all production periods (years) covered in our data set, we can generate crop specific auxiliary yield indices for each farm-year observation in the sample, including those sample farms that did not produce a particular crop in one or several years covered in our empirical analysis. In addition, considering that the model in Equation (1) estimated using Conley's HAC estimator controls for unobserved farm heterogeneity, heteroskedasticity, and spatial and serial correlations, the crop-specific auxiliary indices h_{jit} depend exclusively on weather that is exogenous to the farm production technology.

Subsequently, using auxiliary yield index estimates for specific crops and their respective mean values, we determine for each crop, maize ($j=1$) and winter wheat ($j=2$), the following coarse intervals: $k_j=1$ corresponding to unfavorable weather outcomes and $k_j=2$ corresponding to favorable weather outcomes.

Fourth, we formulate two specifications of the state space, corresponding to crop yield model formulations F1 and F2, each comprising four states of nature defined as follows: *low maize–low wheat*, $s_1=\{k_{j=1}=1, k_{j=2}=1\}$; *low maize–high wheat*, $s_2=\{k_{j=1}=1, k_{j=2}=2\}$; *high maize–low wheat*, $s_3=\{k_{j=1}=2, k_{j=2}=1\}$; and *high maize–high wheat* $s_4=\{k_{j=1}=2, k_{j=2}=2\}$.[26] Henceforth, we refer to the respective state space specifications as F1 and F2. We assign each farm-year observation a specific state of nature using corresponding auxiliary yield index values. Subsequently, we generate four dummy variables corresponding with crop-specific weather outcomes and four dummy variables corresponding with the aforementioned four states of nature. This procedure is exemplified in Table A1 of the Appendix.

Finally, we employ both specifications of the states of nature, F1 and F2, to specify the TFE state-contingent stochastic frontier model presented in Equation (16). We refer to the corresponding models as SC1 and SC2. To test the null hypothesis of an output-cubical technology, we test the SC1 and SC2 models against a standard Cobb–Douglas TFE stochastic frontier model (CD) with a total of four inputs—namely, total farmland, labor, capital, and materials—and a time variable, which is a restricted formulation of SC1 and SC2.

3.8 | Results

Table 2 presents the estimates of the following three TFE stochastic frontier models: the CD model and two SC models formulated using two alternative specifications of states of nature. SC1 corresponds with states' specification F1 based on the auxiliary yield indices derived using the crop yield

TABLE 2 Stochastic production frontier estimates: true-fixed effects estimator.

			State-contingent TFE models			
	Cobb–Douglas TFE model (CD)		SC1: States' specification F1		SC2: States' specification F2	
Variable	**Coeff.**	**Std.err.**	**Coeff.**	**Std.err.**	**Coeff.**	**Std.err.**
$\ln A_2$: *low maize–high wheat*	-	-	0.078	0.031	0.061	0.030
$\ln A_3$: *high maize–low wheat*	-	-	−0.048	0.042	−0.069	0.041
$\ln A_4$: *high maize–high wheat*	-	-	−0.049	0.046	−0.047	0.047
γ_1: labor	0.102	0.021	0.099	0.021	0.098	0.021
γ_2: capital	0.088	0.014	0.088	0.014	0.083	0.014
γ_3: materials	0.243	0.024	0.225	0.024	0.222	0.024
θ: total land	0.408	0.038	0.343	0.039	0.354	0.039
δ_{11}: land maize in *low maize*	-	-	0.061	0.014	0.059	0.013
δ_{12}: land maize in *high maize*	-	-	0.091	0.013	0.090	0.014
δ_{21}: land wheat in *low wheat*	-	-	0.009	0.007	0.010	0.007
δ_{22}: land wheat in *high wheat*	-	-	0.016	0.007	0.017	0.007
Year fixed effects	yes		yes		yes	
σ_u	0.149	0.010	0.153	0.009	0.145	0.009
σ_v	0.208	0.005	0.199	0.005	0.203	0.005
LR test (H0: $\boldsymbol{\delta} = 0$)	-		90.8***		73.0***	

Note: SC1 corresponds with the state formulation F1 that is based on the maize yield model presented in Table A2-1, whereas in SC2, states of nature are formulated using the maize yield model F2 in Table A2-2 in the Appendix. In both F1 and F2, the states are defined using the same winter wheat yield model (s. Table A3 in the Appendix); δ_{11} (land maize in *low maize*) captures output responses to land allocated to maize in states s_1 : *low maize–low wheat* and s_2 : *low maize–high wheat*, δ_{12} (land maize in *high maize*) does it for states s_3 : *high maize–low wheat* and s_4 : *high maize–high wheat*, δ_{21} (land wheat in *low wheat*) measures output elasticity to land allocated to winter wheat in states s_1 : *low maize–low wheat* and s_3 : *high maize–low wheat*, and δ_{22} (land wheat in *high wheat*) is associated with marginal productivity of land allocated to winter wheat in states s_2 : *low maize–high wheat* and s_4 : *high maize–high wheat*.
Note: *** statistically significant at the 1% significance level.
Source: Own estimates.

models that employ temperature and precipitation variables for crop-specific phenology periods (Tables A2-1 and A3 of the Appendix). SC2 utilizes states' specification F2, for which the auxiliary yield index for maize is computed using the estimates of the degree-days' model formulation for this crop (Tables A2-2 of the Appendix). For winter wheat, we utilize in F2 the same auxiliary yield index as in F1.

The likelihood ratio test rejects H0: $\delta_{jr_j} = 0 \left(\forall j \, \text{and} \, \forall k_j\right)$ at 1% significance level for both state-contingent model formulations, implying the presence of substitutability of output across the identified states of nature. Akin to NOQ (2011), we interpret this result as a rejection of the hypothesis of an output-cubical technology.[27]

Most parameter estimates for SC1 and SC2 are highly statistically significant and have the expected signs. The $\ln A$ parameters corresponding to individual states of nature are statistically insignificant for states of nature s_3 : *high maize–low wheat* and s_4 : *high maize–high wheat*.[28] However, the reduced model formulations, where the $\ln A$ parameters are assumed to be zero (except for the reference state of nature), were rejected in favor of the full model.

The output elasticity estimates for labor and capital in SC1 and SC2 exhibit magnitudes that are similar to those in the CD model—all evaluated at the sample averages. The supply elasticities of the materials input are lower for the both state-contingent model formulations. Because materials use usually shows a certain degree of association with land use decisions as well as production

TABLE 3 Estimates of supply response elasticities and marginal rates of technical substitution (MRTS).

	Cobb–Douglas TFE model (CD)	State-contingent TFE models: SC1: States' specification F1	State-contingent TFE models: SC2: States' specification F2
Elasticities of output w.r.t.			
Labor	0.102***	0.099***	0.098***
Capital	0.088***	0.088***	0.083***
Materials	0.243***	0.225***	0.222***
Land[a]	0.408***	0.426***	0.437***
Land maize: *low maize*	-	0.526***	0.532***
Land maize: *high maize*	-	0.615***	0.626***
Land wheat: *low wheat*	-	0.342***	0.354***
Land wheat: *high wheat*	-	0.402***	0.416***
Land *other farm output*	-	0.343***	0.355***
Land under maize and wheat[b]			
s_1 : *low maize–low wheat*	-	0.442***	0.451***
s_2 : *low maize–high wheat*	-	0.469***	0.479***
s_3 : *high maize–low wheat*	-	0.491***	0.503***
s_4 : *high maize–high wheat*	-	0.518***	0.531***
MRTS for land allocations			
$s_2 - s_1$[b]	-	1.061***	1.062***
$s_3 - s_1$[b]	-	1.110***	1.114***
$s_4 - s_1$[b]	-	1.171***	1.176***
High maize–low maize[c]	-	1.169***	1.177***
High wheat–low wheat[c]	-	1.174***	1.174***
Wheat–maize[d]	-	0.788***	0.803***
Other farm output-maize[d]	-	0.509***	0.519***
Other farm output-wheat[d]	-	0.647***	0.647***

Note: *** statistically significant at the 1% significance level.
[a]Average output elasticity for the total land input; for models SC1 and SC2 measured considering land allocation to the three considered outputs and corresponding output elasticities (evaluated at sample averages).
[b]Measured for land input allocated to maize and winter wheat.
[c]Measured for land allocated to respective crop.
[d]On average, over all states of nature.
Source: Own calculations.

uncertainty, this outcome for a production technology representation that explicitly accounts for land allocation decisions across different groups of crops and states of nature appear to be reasonable.

The estimates of the δ-parameters, measuring how farm output in corresponding states of nature responds to land allocation to crop j, are highly significant except δ_{21}, which correspond to land allocated to production of winter wheat in the states of nature accommodating the *low wheat* weather outcome. This result implies that in both the state-contingent model formulations this parameter does not significantly differ from the corresponding parameter estimate for the total land variable, θ.[29]

Table 3 presents the estimates of supply response elasticities for all inputs, cropland allocated to maize and winter wheat under different states of nature, and land allocations to each study crop under the corresponding favorable and unfavorable states of nature; all evaluated at the sample averages.

The output elasticity estimates for the total land input are higher in both SC1 and SC2 than for the CD model. Across SC1 and SC2, the estimates of the supply elasticity for land allocated to maize is noticeably higher for the two states of nature accommodating the weather outcome *high maize* (i.e., s_3 : *high maize-low wheat* and s_4 : *high maize-high wheat*) than for the two states associated with the weather outcome *low maize* (i.e., s_1 : *low maize–low wheat* and s_2 : *low maize–high wheat*). This outcome is also valid for the land allocated to winter wheat under the states accommodating different weather outcomes for this crop. The MRTS estimates for the land input allocated to maize indicate that one hectare of this crop in the maize favorable states can substitute for 1.17 and 1.18 hectares of maize in the states characterized as unfavorable for producing this crop, according to the estimates obtained for SC1 and SC2, respectively. The respective estimates for wheat are 1.17 for both models. These findings suggest that, for both study crops, implicit producers' prices for land are higher in the states identified to be favorable compared to those that are considered as unfavorable for each crop.

The estimates of MRTS for land allocated to different crops are similar across SC1 and SC2, and indicate that, when evaluated at the sample averages, one hectare of winter wheat substitutes for 0.79–0.80 hectares of maize without affecting the amount of total farm output produced. The MRTS estimates for *other farm output* and maize are considerably lower: 0.51 (SC1) and 0.52 (SC2). Respectively, one hectare of winter wheat has a higher implicit price than one hectare of *other farm output*, when evaluated at the sample averages. These results indicate that the marginal land productivity for maize is higher than that for winter wheat, and, for both maize and wheat, marginal land productivity is higher compared to that for land allocated to other crops (produced in Hungarian cereal farms). This finding is indeed in line with the empirical evidence.

The MRTS estimates for the cropland under maize and wheat across s_2, s_3, and s_4 compared to the reference state of nature, s_1, are all lower than the MRTS estimates expressing differences in marginal productivity of land allocated to each of the two study crops between the corresponding favorable and unfavorable states for each crop. The MRTS estimates across the states of nature vary between 1.05 and 1.17 for SC1, and 1.06 and 1.17 for SC2. These estimates are lower than the MRTS estimates *high maize–low maize* and *high wheat–low wheat* expressing marginal substitution of land under different states of nature for single crops, except the MRTS estimates for $s_4 - s_1$, which is reasonable since the latter measures MRTS for the two extreme states of nature. This result implies the presence of substitution effects between two study crops' outputs within states of nature.

Overall, our land output elasticity estimates show rather moderate differences across the formulated states of nature, which results in only moderate MRTS estimates. There are at least three reasons for this outcome. First, we represent the production technology using a production function formulation that limits our capacity to measure substitution in the context of a multiple output production. Second, we specify rather coarse states of nature. Third, producers may allocate more inputs to states of nature that they believe are more probable. A more risk averse producer may tend to allocate more efforts to unfavorable states to be closer to the equal-output ray in the state-contingent output space, that is, to attempt to increase the output across favorable and unfavorable states in a proportional manner (Chambers & Quiggin, 2000). However, by doing so, they may forgo opportunities for output substitution between states of nature. In fact, our sample farms demonstrate reasonably diversified production plans. Crop diversification is indeed an important risk management instrument in Hungarian agriculture and may have helped our sample farms to smooth the aggregate output across the states of nature.

The parameter estimates related to the technical inefficiency component exhibit high statistical significance. H0: $\sigma_u = 0$ is rejected at the 1% significance level for all three TFE models. This indicates the presence of technical inefficiency (Table 2 and Table A6 of the Appendix). However, we did not find significant differences between the technical efficiency distributions for the CD model and each of the two SC models. Note, that the estimates of technical efficiency presented here refer to short-run or transient technical efficiency (Colombi et al., 2014; Kumbhakar et al., 2014).

4 | CONCLUDING REMARKS

The fact that stochastic output realizations in single production periods are associated with one of the many possible states of nature and, therefore, incompletely reflect the effect of production uncertainty, poses a serious identification problem for modeling state-contingent production technology. Furthermore, when identifying relevant stochastic events to map production uncertainty, researchers are confronted with a similar problem to that of a conditioning-on-observables identification strategy.

In this study, we present how a reduced-form approach for evaluating the impact of weather shocks on crop yields—fixed-effects crop yield models—can be accommodated with a structural approach—the state-contingent technology model—to address the well-known identification problem. We demonstrate that the proposed empirical strategy enables a consistent mapping of production uncertainty in the context of multiple output production, respects panel data structure, and allows to control for unobserved farm heterogeneity.

Our empirical analysis, implemented using Hungarian national FADN data, exemplified that production uncertainty significantly influenced the input allocation decisions of Hungarian grain producers during the study period. The null hypothesis of an output-cubical technology was rejected at the 1% significance level for both the state-contingent technology model formulations used in the study.

Some aspects of modeling a state-contingent multiple output production technology were not addressed in this study and consequently require further research. In our empirical application, we employed a production function technology formulation, which may have caused a biased representation of a multiple output production technology and substitution effects across states of nature. Furthermore, we focused solely on weather-related production uncertainty and did not consider other important sources of uncertainty in agricultural production (e.g., risk of pest and diseases, and price uncertainty). However, the approach can be extended to account also for these types of uncertainty.

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ENDNOTES

[1] At the same time, reduced-form models are known to fall short in drawing correct inferences about the effects of policies and other changes in the environment affecting the underlying structure of a problem or process (Cho & Antle, 2023; Provencher, 1997). In their recent review of research on risk management in agriculture, Tack and Yu (2021) acknowledged the progress that has been made in reduced-form approaches. Concurrently, they emphasized the need for innovative structural approaches accommodating advances made in reduced-form approaches.

[2] For example, in their *ex ante* analysis of technology adoption in hemp production, Cho and Antle (2023, pp. 3–4) argue that many policy aspects including adaptation to climate change involve assessment of new technologies in new or future settings where historical data have only limited relevance.

[3] This can also be the case in the presence of technical efficiency.

[4] For each of three random variables used in the empirical application of their ex ante cost function including the agricultural output price index, they estimate time series models and combine them with Monte Carlo simulations to derive for each random variable and each period 500 quasirealizations. Subsequently, they compute the random variate for the low (high) event as the average below (above) the median of simulated output price values for corresponding periods.

[5] The authors use meteorological observations at the province level (NOQ, 2011).

[6] NOQ (2011) formulate three states of nature each corresponding to one of the three crops/outputs considered (i.e., a state of nature that is favorable for producing Crop 1, a state that is favorable for producing Crop 2, and a state of nature that is favorable for producing Crop 3).

[7] The SEM estimator has some advantages and disadvantages compared to Conley's HAC estimator. Additional details regarding this subject can be found in Ortiz-Bobea (2021).

[8] Note, the number of intervals may vary from crop to crop.

[9] In the example, if we had increased the number of pertinent weather outcomes/auxiliary index intervals for only one of the three crops to three, the number of states of nature would have increased to a total of 12.

[10] In our empirical application of the proposed approach, we have reduced the scope of our analysis to weather-related production uncertainty because we do not have data on pest and disease damages for sample farms.

[11] This model can also be found in O'Donnell and Shankar (2009).

[12] Rasmussen (2003, p. 459) provides the following definition of a state-allocable input "an input that may influence output in two or more states of nature, and which may be allocated (ex ante) to different states of nature." Furthermore, Rasmussen proposes drawing distinction between strictly state-allocable (or state-specific input)–influencing production in one single state only–and not strictly state-allocable inputs–such that may influence output in different states of nature in dissimilar ways.

[13] Land is often the only production factor, for which farm accounting data contain records on its allocation to production of different farm outputs.

[14] Shankar and Quiggin (2013) extended OCQ's (2010) model to a state-general state-contingent specification of technology. By assuming the rational behavior and technical efficiency of risk-neutral firms that maximize a welfare function using (individual) subjective probabilities about future states of nature, they develop an econometric methodology that allows the estimation of decision makers' subjective probabilities and the parameters of stochastic production technology in the presence of two states of nature, from which only one is observed.

[15] We have slightly adjusted the original notation used by O'Donnell and Griffiths (2006) to ensure consistency of the notation used herein.

[16] Although the approach by NOQ (2011) does not model a multiple output production technology explicitly, under certain (restrictive) assumptions, it may be applied to study substitution between state-contingent outputs, in particular, by using information about farmers' land allocations to production of different crops. According to Chambers and Just (1989), under the assumption of an input-nonjoint technology, it is reasonable to expect that a profit-maximizing producer will allocate a "quasi-fixed but allocatable input" optimally across different crops, that is, equate the shadow prices of the input across crops. Subsequently, assuming the consistency of production decisions under uncertainty with profit maximization (Chambers & Quiggin, 2000) and applying the first-order profit-maximization condition, it can be demonstrated that the slope of the marginal rate of technical substitution line for two alternative land input allocations should be equal to the slope of the marginal rate of the substitution line for corresponding outputs. Moreover, we believe that there is a small but nontrivial advantage of measuring the output substitution between states of nature using observations regarding producers' ex-ante input demands instead of ex-post output realizations. Particularly, observations regarding producers' ex-ante input allocations could be considered a more informative data source than ex-post output realizations. The advantage of using data on producers' ex-ante input allocations has already been recognized for some time. Considering that information on farmers' expected output levels are unknown and unobservable to researchers, a number of insightful contributions (Chambers & Serra, 2018; Chavas, 2008; Moschini, 1988; Pope & Just, 1996, 1998; Pope & Chavas, 1994) have explored the options for estimating ex-ante cost functions. Further, LaFrance and Pope (2010) have examined the necessary and sufficient conditions for variable input demands using observational data on input prices, quasifixed inputs, and total variable cost.

[17] For example, in the case of two crops, each with two selected weather outcomes—"favorable" and "unfavorable," we can distinguish between two pairs of states of nature for each crop: two states with the weather outcome "favorable" and two states with the weather outcome "unfavorable."

[18] We present the FLEX0 model in NOQ (2011) using the same notation as in the original study, that is, without using farm and time subscripts.

[19] This model is essentially an extension of the Cobb–Douglas production function model and assumes a unitary elasticity of substitution between different factor inputs. We also tried to estimate the model presented in Equation (13), which is a CES representation of production technology. Unfortunately, we could not obtain convergence for this model formulation. Both the CES and Cobb–Douglas production functions place some restrictive assumptions on the production technology. The CES specification assumes the elasticity of substitution to be the same across all inputs, whereas the Cobb–Douglas specification assumes the elasticities of substitution across all inputs to be equal to 1. Hence, both functional forms may not well represent the production technology. Accordingly, our model estimates presented in the next section may be biased. We thank one of the referees, who drew our attention to this aspect of our empirical application.

[20] Agri4Cast provides data from weather stations interpolated on a 25 × 25 km grid.

[21] We used expert information on the most important phases in the phenology of specific crops and relevant sets of weather variables. Considering the relatively short period covered by our farm data, we assume that phenological phases did not demonstrate substantial changes for both study crops during the study period.

[22] We found both growing and heat degree-days variables to provide a better statistical fit compared to lower or higher upper threshold values. Although we do not estimate the piece-wise linear model proposed by Schlenker and Roberts (2009), our results for maize are consistent with the empirical findings obtained in their study. Particularly, when estimating their piece-linear model for different groups of regions in the U.S., they found a slightly higher threshold of 30°C for the northern regions of the country. Notably, our sample farms are located between 45.75° N and 48.41° N latitudes, which is further north than most U.S. regions.

[23] We also estimated crop yield models for two further crops grown by sample farms, namely, sunflowers and raps. However, they also provided low explanatory power. This may be because of strong specialization of Hungarian cereal producers in maize and winter wheat. Notably, substantially fewer sample farms produced sunflower and raps than maize and winter wheat. Moreover, our farm data demonstrate that both crops were rather irregularly grown by the sample farms. These aspects of our empirical data may have impeded the identification of the impacts of interannual weather variation on sunflower and raps yields. The low explanatory power of the model employing the land productivity index for the *other farm output* variable may be related to the diversification effect because this output variable comprises several crops/activities.

[24] This outcome may be related to the fact that temperature regimes in fall and spring are comparatively favorable for winter wheat in Hungary. Therefore, temperatures in these seasons seldom exceed critical thresholds. Indeed, we found the average degree days for all three temperature intervals above 0°C determined in Tack et al. (2015) to be substantially lower for our sample farms than those in in their study.

[25] The final model specifications employ weather variables tested to significantly improve the explanatory power of the respective model.

[26] The conditional mean function $E[(y|\boldsymbol{x})]$ is the optimal predictor for quadratic loss functions, whereas the conditional median is the optimal predictor for estimators based on the absolute error loss criterion (Cameron & Trivedi, 2005). Considering that we generate auxiliary yield indices using yield model estimates obtained by applying Conley's HAC estimator, which has a quadratic loss function, we use farm means of auxiliary indices to discriminate between the two coarse index intervals for the respective crop.

[27] We also estimate production technology parameters of the model in Equation (16) using an iterated system generalized method of moments (GMM) estimator (Arellano & Bover, 1995; Blundell & Bond, 1998; Hansen et al., 1996; Hansen & Lee, 2021). In the GMM model, we assume that land and labor are exogenous, capital and materials are predetermined, and specific cropland allocations are endogenous. In addition to standard GMM instruments, that is, lagged explanatory variables, we use individual farms' maize and wheat prices (normalized by the national fertilizer price index) lagged one period back as instruments to control for the endogeneity of farms' crop land allocations. The system GMM model estimates are in general in line with those obtained using the TFE estimator. They also reject the null hypothesis of an output-cubical technology for both SC1 and SC2 (Table 2 and Table A4 in the Appendix). The GMM estimates of the output elasticities for the total land input and labor have similar magnitudes to the corresponding TFE model estimates. However, the supply elasticities for capital and materials, which are treated as predetermined variables in the GMM model, are significantly higher for both SC1 and SC2 than the corresponding estimates obtained with the TFE estimator (Table 3 and Table A5 in the Appendix). In addition, the GMM model estimates indicate greater differences in output elasticities for both maize and wheat land allocations between the corresponding favorable and unfavorable states of nature, which is reasonable given the use of instruments in the GMM models. Accordingly, GMM model estimates suggest the presence of greater substitution effects for crop specific land allocations across states of nature. Note, that residuals of a GMM model can be used to estimate stochastic frontier models. See for example Guan et al. (2009) or Bokusheva et al. (2023).

[28] OCQ (2010, p. 3) provide the following potential interpretations for the $\ln A$ parameters: (i) technical parameters that are specific to the production of output in a particular state of nature; (ii) ex-post realizations of an unobservable scalar random variable that is within nature's control.

[29] Accordingly, we do not use this parameter for measuring supply elasticities of land in the states of nature accommodating unfavorable weather outcomes for wheat.

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